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Multi-agent-based energy management of multiple grid-connected green buildings

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A R T I C L E I N F O

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A B S T R A C T

Integration of distributed energy resources (DER) in electrical microgrids introduces residential green buildings (RGB) with a promising decrement in fossil fuel consumption. This novel concept compromises numerous challenges such as controlling DERs and consumers in a home microgrid (H-MG), based on historical data and market clearing price (MCP), which requires multi-objective analysis and an energy management system (EMS). Initially, tremendous issues emerged when integrating these systems with RGBs. Therefore, multi-agent systems (MAS) are capable of utilizing parallel computing as a control method, where each RGB represents as an agent with independent decision-making capability, while productively cooperating with other agents. In this paper, an effective EMS has been presented with MAS (EMS-MAS) for DER in a neighborhood grid, accompanied by several RGBs. The RGB includes controllable and uncontrollable devices by residents and building management systems (BMS), where controllable devices are HVAC and home appliances (e.g: dishwashers, washing machines), and uncontrollable devices are lighting systems, flexible heating and cooling demands, respectively, along with several electrical loads (e.g: lighting system, A/C, refrigerator, etc.) and thermal loads (e.g HVAC systems, water heater, ovens, etc.) with retailers who sell and buy electricity to/from residents. Finally, the results confirm that the proposed model has significantly enhanced the overall energy efficiency and the profit of individual RGBs, and optimally managed the devices in RGBs while encouraging demand response (DR) load programs, retailers and MCP reduction.

1. Introduction

High penetration of distributed energy resources (DERs) necessitates the proper management and control of energy. In particular, two control strategies have been described such as generation side and demand side management [1–3]. Demand side management is immensely appropriate for residential green buildings (RGB) due to the financial incentives [4–7]. However, the most challenging

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Nomenclature

Acronyms

RGB	residential green building
AEL	aggregated electrical load
ATL	aggregated thermal load
CHP	combined heat and power
DR	demand response
DW	dish washer
DER	distributed energy resources
DSO	distributed system operator
EES	electrical energy storage
ESP	electrical solar panel
EV	electrical vehicle
GB	gas boiler
HHW	heat and hot water
H-MG	home Microgrid
MCP	market clearing price
MO-TE	market operator based on transactive energy
NG	natural gas
NRL	non-responsive load
PV	photovoltaic
REF	refrigerator
RET	retailer
RLD	responsive load demand
SBP	system buy price
SSP	system sell price
SOC	state-of-charge
TD	thermal dump
TES	thermal energy storage
TSP	thermal solar panel
TE	transactive energy

Indices

e / h / t / i	electricity/ heat/ time steps/ number of H-MG
$j \in \{CHP, TSP\}$	thermal DERs
$k \in \{ESP, CHP\}$	electrical DERs
$m \in \{DW, EV, REF, AEL\}$	electrical consumers
$l \in \{HHW, ATL, TD\}$	thermal consumers

Constant values

$\underline{SOC}^x$, $\overline{SOC}^x$, $\overline{P}^{x,e/h}$, $\underline{P}^{x,e/h}$	minimum/ maximum SOC/ power of X during charging and discharging mode, $x \in \{ES+, ES-, EV+, EV-, TES+, TES-\}$
$E^{\mathrm{Tot},x}$	total value of X capacity
$\underline{T}^y$, $\overline{T}^y$	minimum/ maximum value of y temperature, $y \in \{REF, HHW\}$
$\underline{P}^j_{e/h}$, $\overline{P}^j_{e/h}$	minimum/ maximum electrical thermal power j
T^y_{INI}, T^{RED}, T^{INC}	initially temperature/ the amount of temperature reduction each time the REF compressor is turned on/ the amount of temperature increase each time HHW is turned on
$\zeta^j_{e/h}$	electrical and thermal efficiencies j
$\underline{T}^{\mathrm{HHW}}$, $\overline{T}^{\mathrm{HHW}}$	minimum/ maximum values of temperature in HHW
$\underline{E}^x$, $\overline{E}^x$	minimum/ maximum values of energy in x

$\underline{\pi}^{z}$, $\overline{\pi}^{z}$	minimum/ maximum values of price bids by z, z∈ $\{j, k, m, l\}$
π_t^{NG}	natural gas price
$\tilde{\lambda}_t^{\text{MCP}}$	MCP prediction value during each time interval t (£/kWh)
Decision variables	
X_t^{Ret}, X_t^{ES}, X_t^{TES}, X_t^{DR}	binary variable of retailer, electrical energy storage, thermal energy storage, demand response
$P_t^{m,e}$, $P_t^{l,h}$	consumed electrical/ thermal power by m/ l at time t
$P_t^{j,e}$, $P_t^{k,h}$	electrical/ thermal power generated by j/ k at time t
$\pi_t^{z,e}$, $\pi_t^{z,h}$	electrical/ thermal price bids by z at time t
$P_t^{\text{Ret+,i}}$, $P_{t,e}^{\text{Ret-,i}}$	electric power sold/ bought by H-MG i to/from the retailer
$\lambda_t^{\text{MCP},s}$	Market clearing price by using the S optimization method (£/kWh) S=1: particle swarm optimization (PSO) S=2: harmony search (HS) S=3: differential evolution (DE) algorithm S=4: bat algorithm (BAT)

objectives could be identified as, defining the optimum value of DERs, loads shifting, supply and demand balancing, and enhancing the total revenue. Similarly, an effective energy management system strongly depends on the RES structure presented in the neighborhood grid, DER and local energy storage (ES), and communication between H-MGs and retailers, in order to monitor and investigate the behavior of the system and effective responses to different scenarios. The multi-agent system (MAS) with the properties such as self-learning, asynchronous and parallel computing, scalability, re-development, and re-usability, could influence the performance of RGBs [8,9]. In MAS, each part of the system is controlled by an autonomous individual smart unit that follows its own defined goals. These units consist of highly interdependent operations and efficient mutual communication to optimize the decisions and the ultimate results.

Although, enormous contributions were widely presented on electrical energy management strategies with DER and ES for RGBs, the studies with the peer-connected RGBs (multiple RGBs in the neighborhood systems) to minimize the fossil energy consumption, have not been considered in the literature. However, in the proposed model, the RGB with the neighborhood of other RGBs has formed a set of H-MGs, where each RGB is independently managed and controlled by a smart agent, while cooperating with others to share power and enhance the revenue. In this concern, the chief downsides (DS) in the previous studies could be outlined as

- **DS1**: Non-existence of a method to exchange energy through the neighborhood RGB resources and, supply the consumer's load demand from generated energy in RGBs [10–14].
- **DS2**: Absent to design a model with the participation of consumers in demand response (DR) program and present a solution to calculate market clearing price (MCP) [15–22]. However, in the proposed model, MCP value was calculated by Nash equilibrium point, which is the optimum capacity, with the contribution of all the players in the market.
- **DS3**: Absence of a solution, which is based on optimization algorithms to implement and evaluate the optimum clearance value of the market process while introducing a pay-off for all the market players [23–26].
- **DS4**: Not presents a solution to determine the strategy and behavior of residential customers as prosumers, and absent to introduce a strategy for the consumers to participate in the market [27–29].
- **DS5**: Non-existence of an algorithm to reach the collective profit of all the players and dealing with the behavior of the players with different objectives in the optimization process [30,31].

This paper proposes a strategy to obtain the optimum energy management by MAS theory for the H-MGs in the neighborhood structure. Each H-MG is defined as an agent with several properties such as automation, adaptability, and simultaneous interaction with other agents. Moreover, the proposed model has facilitated several types of DERs to increase the profit for all the players by optimization algorithms. On the consumer's side, the residential customers represent MCP as prosumers and consumer during DR program and the H-MGs earn an additional profit by selling the surplus energy to the neighbors and retailers. Nevertheless, the energy exchange between RGBs has influenced the consumer accessibility to energy generation resources, which results to escalate competition between players in the electricity market. In addition, DR strategy has contributed to reduce the peak load and gain the overall profit, by shifting load demand from peak hours to non-peak hours. For example, the MCP has increased during peak hours, whereas the MCP has reduced in the non-peak hours, to optimize the load demand in the system. Several literature were investigated implementing the EMS for H-MG with the contribution of MAS method [7,9,32,33]. Overall, the main research contributions (RC) of this study could be highlighted as follows:

- **RC1**: A navel framework, based on MAS is presented to create a smart structure between H-MGs to exchange energy and supply load through the neighborhood RGB resources (Eliminates **DS1** and **DS2**).

- **RC1**: In the presented framework, for controlling and managing power in the neighborhood grids, DR strategy is considered with the consumers and prosumers involvement for an effective MCP that increases overall profit by shifting demand from on-peak price to off-peak price (Eliminates **DS3**).
- **RC1**: Introduces a comprehensive and smart algorithm to exchange power through the resources among H-MGs, and the possibility of consumers load supply by reliable access to the DERs of other H-MGs (Addresses **DS4** and **DS5**).

2. A review of MAS

MAS is an intelligent autonomous system with computerized entities called agents. An agent is located in an environment which could share autonomous actions to solve conflict issues. These agents are able to interact with its background and also with each other to accomplish the delegated objectives. On the other words, MAS is a framework for optimizing the activities of agents by combining artificial intelligence and mathematical tools for decision-making [34]. The agents are divided into three categories such as passive agent, active agent, and cognitive agent [12,13,35,36]. The passive agent or reactive agent is called the agent without the target, which has low communication capacity and respond to a commanded action. The active agent can be described as agent with goals, while the complex calculations are controlled by the cognitive agent which is capable of mutual communication.

Agent environment is defined as an external section to entities which communicates, assess, and investigates the system. The three main categories of agent environments are virtual, discrete, and continuous. Virtual environments are dealing with artificial intelligent (AI) and, discrete agent environment is introduced when there are a finite number of actions. Similarly, if the numbers of agent performances are unlimited, it is to be explained as a continuous agent environment. The agent environments are further grouped according to the determinism, accessibility, episodic/non-episodic, and static/dynamic properties. Determinism refers to the accuracy of the action while accessibility defines the possibility to gather complete details. Further, when the future actions are independent from the present actions, it is described as an episodic environment, whereas in non-episodic background, the future agent's performance is influenced by the current actions. Static and dynamic environments are determined by the nature of changes in the operating conditions.

The advancement of MAS has facilitated numerous advantages in the contemporary world. In particular, the agents in MAS are autonomous, self-aware, and independent which solve complicated situations by dividing them into smaller problems with simplified computations to increase the processing power [37]. Moreover, these agents are capable of local views instead of global views, to maintain the simplicity of the network. Decentralization is one of the key benefits of the MAS where the controlling of the system is distributed to enhance the system's reliability and efficiency. For example, the failure of an individual agent does not result in the overall system failure and entities could simply add or remove from the system without affecting other elements [24,38]. Therefore, these benefits make it ideal for energy management in green buildings.

The applications of the MAS have diversified into enormous fields. Specifically, MAS plays a prime role in AI and graphical applications, transportation, logistics, census, power systems, and smart grids, to balance the dynamic load and enhance the self-healing in the system. The properties of smart agents in H-MGs could be listed as follows [25,28,39,40]:

- Agents are autonomous and self-decision makers.
- They are able to perceive changes in the environment.
- Capable of changing the decisions and consequently modifying the actions according to the existing environmental conditions.
- Agents are able to react in their environment. In other words, they change their environment through their behaviors.
- Agents could communicate with each other in order to enhance the efficiency in a distributed decision system.
- In non-supervisory control, agents consist of a specific level of autonomy to carry out a set of necessary measures, without permission from a central controller. In fact, this autonomy dependents on defined goals for each agent.
- In a large system, the agents share information together to enhance community benefits.
- Agents are accompanied by specific behaviors for fulfilling targeted goals by resources, skills, and services.
- Similar agents contain different behaviors, which are related to their decisions.

3. The structure of EMS based on MAS (EMS-MAS)

The proposed model is an EMS based on MAS. In the structure, several agents have been introduced to interact with each other and gain a common goal. For example, the generation sources, consumers and prosumers presented in a H-MG act as individual agents. Generation agents are responsible to monitor and control power levels and defining the optimum generating point, along with balancing the load between the generation side and the demand side [41]. ES and DR agents are responsible for monitoring SOC condition and controlling the corresponding loads (prosumers) [42,43]. The DR agents are also responsible for load shedding during peak hours. Further, the ES agent's main goal is to ensure that the energy storage system is used optimally to balance the supply and demand of power in the H-MG. The behaviors of the ES agent include monitoring the SOC of the energy storage system, monitoring the demand and supply of power in the H-MG, and controlling the loads to ensure that the energy storage system is used optimally. The ES agent also communicates with other agents in the H-MG to share information about the available power and demand and cooperates with them to achieve the objectives of the MCP. Ultimately, the ES agent plays a crucial role in achieving energy autonomy for the H-MG by efficiently managing the energy storage system and coordinating with other agents to ensure that the system operates in a sustainable and self-sufficient manner. When a DR event occurs, the ES and DR agents are responsible for monitoring the SOC condition of ES systems and controlling corresponding loads (prosumers). They may shed or

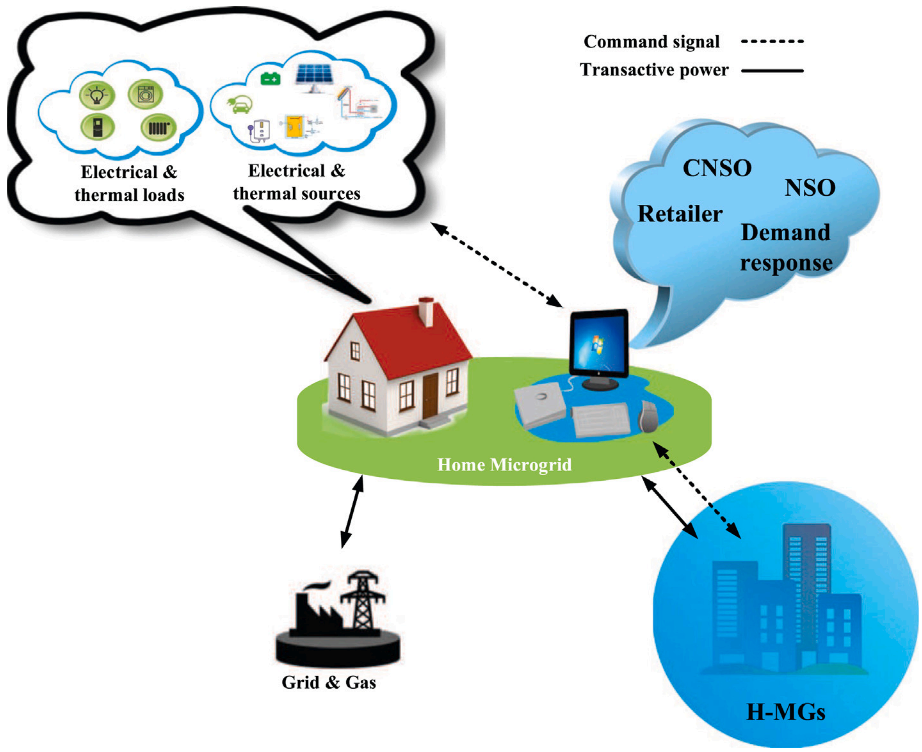


Fig. 1. Information exchange and relation among agents in the MAS structure.

reduce loads in response to the DR event, in order to balance the load and reduce overall power consumption. The shedding of loads is managed through a process called load curtailment, which involves reducing the power consumption of non-critical loads or temporarily switching them off. The shedding of loads is shared among the Home-Microgrids (H-MGs) through a coordinated effort among the ES and DR agents, NSOs, CNSO, and retailers. The ES and DR agents monitor the SOC condition of ES systems and control corresponding loads, while the NSOs communicate information about power generation and consumption to the CNSO agent. The CNSO agent uses this information to evaluate the optimum price bids and define the amount of electrical/thermal energy to be supplied by each NSO, in order to balance the load and ensure that the demand for power is met. The retailers declare the purchasing and selling power to the CNSO agent, who uses this information to make decisions about the ideal biddings in the load distribution system. Ultimately, the shedding of loads is shared among the H-MGs in a way that balances the load and minimizes overall power consumption during the DR event. This coordinated effort among multiple agents helps to ensure the effective implementation of DR and the efficient use of energy resources in the EMS system. As shown in Fig. 1, agents of the MAS in the proposed structure are mutually cooperating to achieve the objectives in the market.

According to the figure, the topology consists of four levels such as retail level, central neighborhood system operator (CNSO) level, neighborhood system operator (NSO) level, and H-MG level. At the H-MG level, generators, consumers and prosumers communicate with NSO operators as cognitive agents to receive information such as generated and consumed power. Therefore, the decision-making information is accessed by NSO. Further, the NSOs, CNSO and retailers perform as reactive agents to share information on surplus power and inadequate power in the H-MG. Thereafter, CNSO agent selects the specific H-MGs with excess power and insufficient power based on the information from the NSOs. The retailer agents distribute the details about power availability and the demand, among buyers and sellers. Ultimately, CNSO agent selects the most appropriate buyers and sellers for heat and electricity according to the offers received from NSOs and retailers. Therefore, it is confirmed that CNSO can work with other agents, such as energy producers, distributors, and consumers, to establish a competitive and fair market for energy trading. To measure and evaluate the optimum price bids, the CSNO can:

- **Define the market rules**: The central system operator can establish rules and regulations for the market, such as the types of energy products traded, the bidding process, and the clearing and settlement procedures.
- **Receive and process bids**: The central system operator can receive bids from energy producers and distributors and process them according to the market rules. The central system operator can use a sophisticated software system to handle the bidding process and ensure that all bids are evaluated fairly.
- **Monitor the market**: The central system operator can monitor the market closely to detect any market manipulation or abuse. The central system operator can use advanced market monitoring tools to analyze market data and detect any unusual trading behavior.

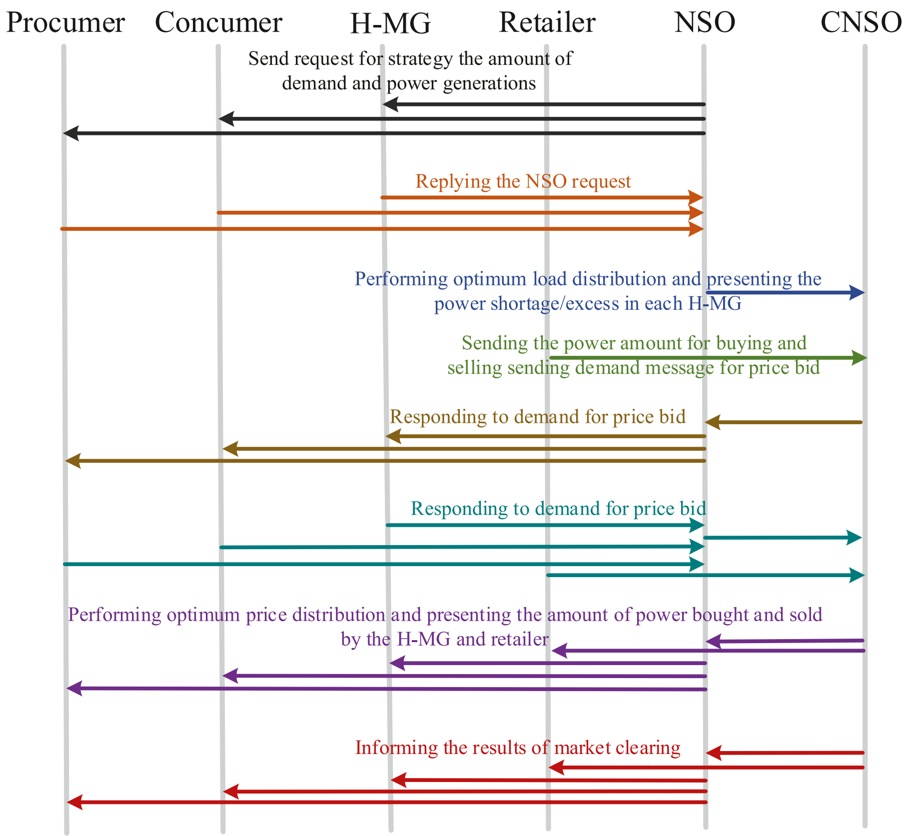


Fig. 2. Method of exchanging information in the proposed MAS.

- **Collaborate with other agents**: The central system operator can collaborate with energy producers, distributors, and consumers to ensure that the market is efficient and effective. The central system operator can work with these agents to set up efficient trading mechanisms, such as auctions or spot markets, that help to ensure fair pricing.
- **Settle trades**: The central system operator can settle trades according to the market rules. The central system operator can ensure that all trades are settled promptly and accurately and that all parties receive their payments or energy products as agreed.

In addition, the CNSO agent also plays a crucial role in promoting energy autonomy by encouraging the use of renewable energy sources and minimizing dependence on non-renewable resources. By continuously monitoring and analyzing data on energy availability and demand, the CNSO agent can help to identify opportunities for the integration of renewable energy sources into the power grid, which can ultimately lead to a more sustainable and self-sufficient energy system. Overall, the CNSO agent is a critical component of an effective energy management system, helping to ensure a reliable and efficient supply of energy while promoting energy autonomy and sustainability. The steps of transferring information between agents are listed (shown in Fig. 2) as follows:

- NSO declares the generating power and the consuming power to communicate with HMGs and consumers.
- Information from the generators, consumers and prosumers are received from NSO.
- NSO distributes optimum load on power generated by the existing DERs in each H-MG and reports the amount of electrical/thermal power availability and the demand to the CNSO. CNSO is responsible for global communication in local NSOs to accomplish load demand in the H-MGs connected to each other. Further, the retailers declare the purchasing and selling power to CNSO.
- CNSO cooperates with other agents to measure and evaluate the optimum price bids.
- CNSO defines the ultimate decisions such as the amount of electrical/thermal energy to be supplied by each NSO and calculates the ideal biddings in the load distribution system, along with informing the final results to other agents for market clearing.

The implementation process of an algorithm with DERs in MO-TE (Market Operator based on Transactive Energy) to reduce the electricity price while increasing the profit in power generation is presented in Fig. 3. This MO-TE structure consists of three main units such as TOAT (Taguchi Orthogonal Array Test) unit, TE (Transactive Energy) unit, and MCP (Market Clearing Price) units. According to Fig. 3, generated solar power, MCP, the load demand, SBP (System Buying Price) and SSP (System Selling Price) are

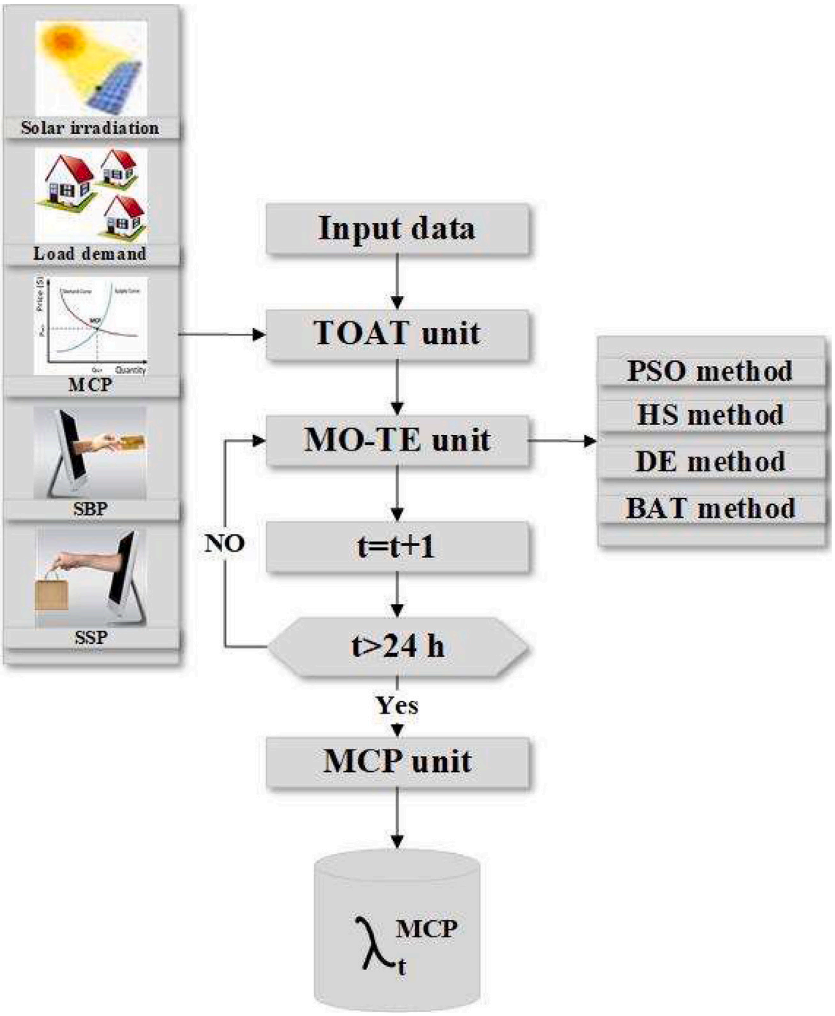


Fig. 3. The process of implementing the proposed algorithm structure.

defined as intermittent parameters, where the TOAT controls the number of test to reduce the unnecessary testing load by providing reliable statistical data. In addition, the MCP unit is responsible for measuring the MCP during each time period.

3.1. Communication protocol

In order to exchange data between agents, Controller Area Network-open (CANopen) protocol can be used as a communication protocol [44]. The CAN bus is a fast field bus control system is used for decentralization, intelligence and network control that can transfer data between different CAN stations [45,46]. The CANopen protocol is a suitable selection for exchanging information between agents due to its expandability, cost-effectiveness in setting up, reliability and fast operation.

3.2. Taguchi orthogonal array test (TOAT) unit

Precise information forecasting is a vital issue in augmenting the accuracy of market structure modeling and planning in a smart system. Nonetheless, implementing this matter is unattainable due to the stochastic nature of effective factors in renewable energy generation, demand quantities, and energy prices. Diverse approaches have been presented to apply the uncertainty elements, including Monte Carlo simulation, information-gap decision theory, and structures based on fuzzy modeling, which all differ in terms of computational volume, time, and the number of application scenarios. One of the swiftest manners to consider uncertainty is Taguchi's orthogonal array testing (TOAT), which diminishes the computation volume and performance time by scrutinizing fewer scenarios. Indeed, orthogonal arrays are employed to analyze the impact of factors on the response of average and variation in Taguchi's designs to achieve a balanced plan that the factor's levels have the same weight. Therefore, each factor's independent assessment is feasible since a distinct factor does not influence the estimation of another one. TOAT, with the least number of scenarios, leads to selecting the optimal test scenarios in the worst case to protect the uncertainty sources in all situations. Besides, it provides the possibility of discrete factors investigation exposing appropriate statistic data in unsure operation space. Hence, by substantial scenario reduction, a robust solution can be accessible. Accordingly, in dynamic optimization problems which apply several repetitions to determine the optimal point and even in designing cases with high sensitivity, utilizing this method saves time effectively. In fact, TOAT's purpose is to create a process that has less volatility and chaos to address instability with little or no control and execute an assured procedure. An orthogonal array is a matrix that is represented as $L_H(B^F)$. H and F represent the number of rows and columns of the matrix, respectively, and B indicates the number of levels of the matrix elements (uncertainty variables). Also, F expresses the maximum number of uncertainty factors examined by the array. This method consists of three primary steps as follows:

- **Step 1**: Opting for the orthogonal matrix according to the number of uncertainty's factors in the problem.
- **Step 2**: Creating n initial test scenarios by using distribution functions.
- **Step 3**: Computing the possibility of occurrence of the generated scenario via employing probability distributions.

3.3. Transactive energy (TE) unit

TE unit has designed by several methods such as particle swarm optimization (PSO), harmony search (HS), differential evolution (DE) and bat algorithm (BAT) methods (see algorithm 1 in Appendix A). Each approach has used electrical and thermal parts for providing initial values to the variables. As observed in algorithm 1 (in Appendix A), when there is a power surplus occurred in the system, the CHP obtain the priority and supplies the required load, and further demand is accomplished by discharging ES. However, when the supplying part of electrical demand is not existing, the absent load demand is calculated and shifted to another time period, where the MCP is comparatively lower. Moreover, the further energy surplus is obtained by purchasing from other retailers. On the other hand, when the excess power is generated in the H-MG with the DR conditions at the initial stage of DR load requirement, the ES is turned into charging mode. Thereafter, the further electrical power produced by each H-MG in the retail market is considered as the disposal power. When there is a thermal power shortage (see algorithm 2 in Appendix A), the H-MG is engaged to provide the thermal service prior to discharging the TES (if TES has the possibility of discharging), otherwise thermal power is purchased from other H-MGs. In contrast, if excess thermal power is occurred, first the TES is turned to charging mode and in case of continued excess generation, the amount of surplus power is supplied to achieve thermal power demand in other neighborhoods H-MG. Overall, the utilization of TE units with the proposed control algorithm helps to improve the energy management system's efficiency and reliability by integrating different energy sources and storage systems, enabling optimal utilization of resources while minimizing operational costs and reducing environmental impacts.

3.4. MCP unit

Market clearing price (MCP) is generally defined as the highest accepted offer. In the electricity market, the value of generated and consumed power for each generation and consumption resource, and the proposed price is revealed to the market operator. In particular, the generated power is arranged in ascending order while the value of the consumed power is sorted in descending order. In this pace, the generators and consumers along with retailers, declare the highest offer price to purchase and sell the power. The ultimate MCP value is defined by this unit for the objective functions of each market player. In addition, MCP creates a relationship between power generation and power consumption. Further explanation regarding this unit has presented by authors in [47]. In addition, by involving consumers and prosumers in the MCP, the framework can help to ensure that the demand response strategies are implemented effectively and efficiently, leading to a more reliable and sustainable energy system, where the DR strategies in the presented framework can help to improve the efficiency, stability, and profitability of the power grid.

4. Power grid under study

The general schematic of the system under study is shown in Fig. 4. The system has *i* number of H-MGs where the electrical and thermal DERs and as well, consumers are installed. Each H-MG consists of electrical and thermal stores, and a set of generation resources including GB, TSP, ESP, CHP along with consumers containing NRL and RLD. In addition, this model consists of controllable and uncontrollable devices, where controllable devices are the devices which can be controlled by the residents and the building management system such as HVAC system and home appliances (e.g: dishwashers, pool pumps, dryers, washing machines). Uncontrollable devices are the devices that cannot be controlled by the residents or the building management system, e.g: lighting system, and flexible heating and cooling demands. Electrical loads are devices operated by electricity, e.g:- lighting, A/C, refrigerators and computers, while thermal load are produce or consume heat such as HVAC systems, water heaters, and ovens.

5. Mathematical implementation of the problem

In this section, problem is mathematically formulated using key components in market structure based on transactive energy. This framework is easily expandable for other electricity distribution systems with high level of consumer participation.

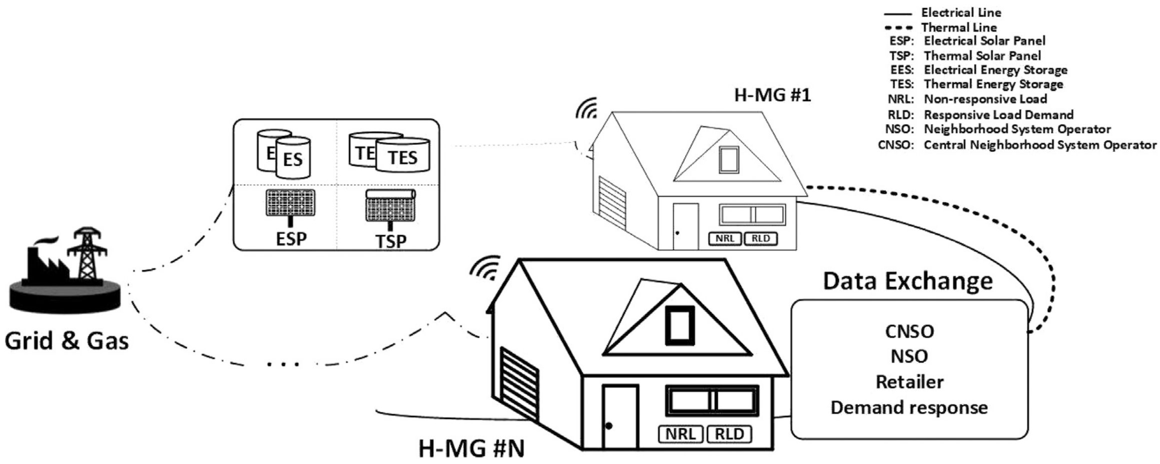


Fig. 4. Schematic of neighborhood system with several H-MGs (continues and black line show the electrical part, gray dash shows the thermal part and the dash-point is related to gas branch).

5.1. Objective functions of the participants in MO-TE

The defined objective functions on maximizing the generators and retailers profit, while minimizing the consumers costs are as follows:

$$\max \sum_{\forall t}\sum_{\forall i}\sum_{\forall j}\sum_{\forall k}(\mathbb{R}^{k,e}_{t,i}+\mathbb{R}^{ES-,e}_{t,i}+\mathbb{R}^{j,h}_{t,i}+\mathbb{R}^{TES-,h}_{t,i} \\ -\mathbb{C}^{j,h}_{t,i}-\mathbb{C}^{TES+,h}_{t,i}-\mathbb{C}^{ES+,e}_{t,i}-\mathbb{C}^{k,e}_{t,i})\times \Delta t \tag{1}$$

$$\max \sum_{\forall t}\sum_{\forall i}(\mathbb{R}^{\text{Ret-},e}_{t,i}-\mathbb{C}^{\text{Ret-},h}_{t,i})\times \Delta t \tag{2}$$

$$\min \sum_{\forall t}\sum_{\forall i}\sum_{\forall l}\sum_{\forall m}(\mathbb{C}^{p,h}_{t,i}-\mathbb{C}^{m,e}_{t,i})\times \Delta t \tag{3}$$

where, $\mathbb{R}^{k,e}_{t,i}$ and $\mathbb{R}^{j,h}_{t,i}$ are accordingly the electrical and thermal revenue from the DERs k and j in the H-MG i. The $\mathbb{R}^{\text{ES-},e}_{t,i}$ and $\mathbb{R}^{\text{TES-},h}_{t,i}$ are respectively the revenue from ES and TES electrical and thermal discharge related to H-MG i at time t. Also, $\mathbb{R}^{\text{Ret-},e}_{t,i}$ and $\mathbb{R}^{\text{Ret+},e}_{t,i}$ are respectively the revenue and cost values of selling and buying electrical power from/to retailer for H-MG i. Alongside, $\mathbb{C}^{p,h}_{t,i}$ and $\mathbb{C}^{m,e}_{t,i}$ are respectively electricity costs related to consumers p and m at H-MG i.

5.2. Technical and economic constraints

This section enlists the various technical and economic constraints.

5.2.1. Total electrical and thermal equilibrium

Eqs. (4) and (5) define that the total power generated by electrical and thermal generators during each time interval is equal to the total demand of electrical and thermal consumers.

$$\sum_{\forall i}\sum_{\forall k}(P^{k,e}_{t,i}+P^{\text{ES-},e}_{t,i}+(1-X^{\text{Ret}}_{t})\cdot P^{\text{Ret-,e}}_{t,i}) \\ =\sum_{\forall i}\sum_{\forall m}(P^{m,e}_{t,i}+P^{\text{ES+},e}_{t,i}+X^{\text{Ret}}_{t}\cdot P^{\text{Ret+,e}}_{t,i}) \tag{4}$$

$$\sum_{\forall i}\sum_{\forall j}(P^{j,h}_{t,i}+P^{\text{TES-},h}_{t,i})=\sum_{\forall i}\sum_{\forall l}(P^{p,h}_{t,i}+P^{\text{TES+},h}_{t,i}) \tag{5}$$

5.2.2. Retailer constraints

Eq. (6) describes the cost of buying electrical power from retailer to H-MG, whereas Eq. (7) represents the offer price range of purchasing the power for H-MG decided by the retailer.

$$\mathbb{C}^{\text{Ret-},e}_{t,i}=\pi^{\text{Ret-},e}_{t,i}\times P^{\text{Ret-,e}}_{t,i} \tag{6}$$

$$0\le \pi^{\text{Ret-},e}_{t,i}\le \lambda^{\text{SBP}}_{t} \tag{7}$$

$$\mathbb{R}^{\text{Ret+},e}_{t,i}=\pi^{\text{Ret+}}_{t,i}\times P^{\text{Ret+},e}_{t,i} \tag{8}$$

$$0 \leq \pi_{t,i}^{\text{Ret}+} \leq \lambda_{t,e}^{\text{SSP}} \tag{9}$$

The revenue of selling electrical power from H-MG i to the retailer is determined by Eq. (8), while Eq. (9) shows the price bid of H-MG i to the retailer.

$$P_{t,i}^{\text{Ret}+,e} \leq X_t^{\text{Ret}} \times \overline{P}^{\text{Ret}} \tag{10}$$

$$P_{t,i}^{\text{Ret-},e} \leq (1 - X_t^{\text{Ret}}) \times \overline{P}^{\text{Ret}} \tag{11}$$

$$\overline{P}^{\text{Ret}} \leq (P_{t,i}^{\text{ESP},e} + P_{t,i}^{\text{CHP},e} + P_{t,i}^{\text{ES-},e}) \tag{12}$$

Lastly, Eqs. (10) and (11) present the exchanged power constraints between H-MG and retailer.

5.2.3. H-MG i constraints

ES and TES constraints in H-MG i

$$\mathbb{C}_{t,i}^{\text{ES}+,e} = \pi_{t,i}^{\text{ES}+,e} \times P_{t,i}^{\text{ES}+,e} \tag{13}$$

$$0 \leq \pi_{t,i}^{\text{ES}+,e} \leq \lambda_t^{\text{MCP,e}} \tag{14}$$

$$\mathbb{R}_{t,i}^{\text{ES-},e} = \pi_{t,i}^{\text{ES-}} \times P_{t,i}^{\text{ES-},e} \tag{15}$$

$$0 \leq \pi_t^{\text{ES-},e} \leq \lambda_t^{\text{MCP},e} \tag{16}$$

where, $\mathbb{C}_{t,i}^{\text{ES}+,e}$, $\mathbb{R}_{t,i}^{\text{ES-},e}$, $\pi_{t,i}^{\text{ES}+,e}$ and $\pi_{t,i}^{\text{ES-},e}$ respectively show the cost, revenue, and price bid resulting from buying/ selling electrical power by ES in H-MG i. Eqs. (17) and (19) represent the maximum and minimum charging/ discharging of ES in H-MG i.

$$\underline{E}^{\text{ES},i} \leq E_{t,i}^{\text{ES},e} \leq \overline{E}_i^{\text{ES}} \tag{17}$$

$$P_{t,i}^{\text{ES-},e} \leq \overline{P}_i^{\text{ES-}} \times X_{t,i}^{\text{ES}}, \quad P_{t,i}^{\text{ES-},e} \geq 0 \tag{18}$$

$$P_{t,i}^{\text{ES}+,e} \leq \overline{P}_i^{\text{ES}+} \times X_{t,i}^{\text{ES}}, \quad P_{t,i}^{\text{ES}+,e} \geq 0 \tag{19}$$

$$P_{t,i}^{\text{ES-},e} \times \Delta t \leq (E_{(t-1),i}^{\text{ES}} - \underline{E}_i^{\text{ES}}) \tag{20}$$

$$P_{t,i}^{\text{ES}+,e} \times \Delta t \leq (\overline{E}_i^{\text{ES}} - E_{(t-1),i}^{\text{ES}}) \tag{21}$$

$$E_{t,e}^{\text{ES},i} = E_{t-1,e}^{\text{ES},i} + (P_{t-1}^{\text{ES}+,i} - P_{t-1}^{\text{ES-},i}) \times \Delta t \tag{22}$$

The maximum charging/ discharging limits determine by Eqs. (20) and (21), where the energy existing in Eq. (22) states energy equilibrium in ES.

$$\mathbb{C}_{t,h}^{\text{TES}+,i} = \pi_{t,h}^{\text{TES}+,i} \times P_{t,h}^{\text{TES}+,i} \tag{23}$$

$$0 \leq \pi_{t,e}^{\text{TES}+,i} \leq \max(\pi_{t,h}^{\text{HHW},i}, \pi_{t,h}^{\text{TD},i}) \tag{24}$$

Eq. (23) explain the cost resulting from buying thermal power by TES in the charging mode, where price bid interval is given in Eq. (24).

$$\mathbb{R}_{t,h}^{\text{TES-},i} = \pi_{t,h}^{\text{TES-},i} \times P_{t,h}^{\text{TES-},i} \tag{25}$$

$$0 \leq \pi_{t,h}^{\text{TES-},i} \leq \min(\max(\pi_{t,h}^{\text{CHP},i}, \pi_{t,h}^{\text{GB},i}), \pi_{t,h}^{\text{TSP},i}) \tag{26}$$

where, $\mathbb{R}_{t,h}^{\text{TES-},i}$ in Eq. (25) is defined the revenue of selling thermal power generated by TES in the discharging mode. The $\pi_{t,h}^{\text{TES-},i}$ in Eq. (26) is represented the price bid range for selling thermal power.

$$\underline{E}^{\text{TES},i} \leq E_{t,h}^{\text{TES},i} \leq \overline{E}^{\text{TES},i} \tag{27}$$

$$P_{t,h}^{\text{TES-},i} \leq \overline{P}^{\text{TES-},i} \times X_t^{\text{TES},i}, \quad P_{t,h}^{\text{TES-},i} \geq 0 \tag{28}$$

$$P_{t,h}^{\text{TES}+,i} \leq \overline{P}^{\text{TES}+,i}, \quad P_{t,h}^{\text{TES}+,i} \geq 0 \tag{29}$$

The TES maximum and minimum charging/ discharging limitations are given in Eqs. (27) to (29).

$$P_{t,h}^{\text{TES-},i} \times \Delta t \leq (E_{t-1}^{\text{TES},i} - \underline{E}^{\text{TES},i}) \tag{30}$$

$$P_{t,h}^{\mathrm{TES+},i} \times \Delta t \leq (\overline{E}^{\mathrm{TES},i} - E_{t-1}^{\mathrm{TES},i}) \tag{31}$$

$$E_{t,h}^{\mathrm{TES},i} = E_{t-1,h}^{\mathrm{TES},i} + (P_{t-1,h}^{\mathrm{TES+},i} - P_{t-1,h}^{\mathrm{TES-},i}) \times \Delta t \tag{32}$$

Eqs. (30) and (31) derive the discharge/ charge maximum limit for the energy in TES, whereas Eq. (32) defines the energy equilibrium in TES.

EV constraints in H-MG i

$$\text{if } X_t^{\mathrm{EV},i} = 1 \Longrightarrow \underline{P}^{\mathrm{EV+},i} \leq P_{t,e}^{\mathrm{EV+},i} \leq \overline{P}^{\mathrm{EV+},i} \tag{33}$$

$$\mathrm{SOC}_t^{\mathrm{EV},i} \leq \overline{\mathrm{SOC}}^{\mathrm{EV},i} \tag{34}$$

$$\mathrm{SOC}_t^{\mathrm{EV},i} = \mathrm{SOC}_{t-1}^{\mathrm{EV},i} - \frac{P_{t,e}^{\mathrm{EV+},i} \times \Delta t}{E_{\mathrm{Tot}}^{\mathrm{EV},i}} \tag{35}$$

$$\mathrm{SOC}_t^{\mathrm{EV},i} = \overline{\mathrm{SOC}}^{\mathrm{EV},i} \Longrightarrow X_t^{\mathrm{EV},i},\ P_{t,e}^{\mathrm{EV+},i} \tag{36}$$

Eq. (34) describes that $\mathrm{SOC}_t^{\mathrm{EV},i}$ of automobile battery during each time interval must be less than its maximum value, wherein, Eq. (35) is the automobile battery power equilibrium constraint.

$$\mathbb{C}_{t,e}^{\mathrm{EV+},i} = \pi_{t,e}^{\mathrm{EV+},i} \times P_{t,e}^{\mathrm{EV+},i} \tag{37}$$

$$0 \leq \pi_{t,e}^{\mathrm{EV+},i} \leq \lambda_{t,e}^{\mathrm{MCP}} \tag{38}$$

The cost of purchasing electrical power by EV is presented in Eq. (37), and (38) shows the scope of the offer of EV price for buying power.

ESP constraints in H-MG i

Eq. (39) presents the limitations of ESP generated power.

$$\underline{P}^{\mathrm{ESP},i} \leq P_{t,e}^{\mathrm{ESP},i} \leq \overline{\mathrm{ESP},i} \tag{39}$$

In addition, Eq. (40) is determined the revenue resulting from ESP generated electrical power, and the corresponding price bid interval is defined in Eq. (41).

$$\mathbb{R}_{t,e}^{\mathrm{ESP},i} = \pi_{t,e}^{\mathrm{ESP},i} \times P_{t,e}^{\mathrm{ESP},i} \tag{40}$$

$$0 \leq \pi_{t,e}^{\mathrm{ESP},i} \times \lambda_{t,e}^{\mathrm{MCP},i} \tag{41}$$

TSP constraints in H-MG i

Eq. (42) derived the generated thermal power income by TSP. Eq. (43) is shown the price bid interval for selling power by TSP.

$$\mathbb{R}_{t,h}^{\mathrm{TSP},i} = \pi_{t,h}^{\mathrm{TSP},i} \times P_{t,h}^{\mathrm{TSP},i} \tag{42}$$

$$0 \leq \pi_{t,h}^{\mathrm{TSP},i} \leq \max(\pi_{t,e}^{\mathrm{TES-},i}, \pi_{t,h}^{\mathrm{CHP},i}, \pi_{t,h}^{\mathrm{GB},i},) \tag{43}$$

CHP constraints in H-MG i

Eq. (44) expresses the CHP power generation limits, whereas in Eqs. (45) and (46), $\mathrm{FU}_t^{\mathrm{CHP},i}$, $\zeta_{e1}^{\mathrm{CHP},i}$ and $\zeta h^{\mathrm{CHP},i}$ are represented fuel, electrical and thermal efficiency of CHP, respectively.

$$\underline{P}^{\mathrm{CHP},i} \leq P_{t,e}^{\mathrm{CHP},i} \leq \overline{P}^{\mathrm{CHP},i} \tag{44}$$

$$P_{t,e}^{\mathrm{CHP},i} = \mathrm{FU}_t^{\mathrm{CHP},i} \times \zeta_{e1}^{\mathrm{CHP},i} + \zeta_{e2}^{\mathrm{CHP},i} \tag{45}$$

$$P_{t,e}^{\mathrm{CHP},i} = \zeta_{e1}^{\mathrm{CHP},i} \times \frac{P_{t,h}^{\mathrm{CHP},i}}{\zeta h^{\mathrm{CHP},i}} + \zeta_{e2}^{\mathrm{CHP},i} \tag{46}$$

$$\mathbb{C}_t^{\mathrm{CHP},i} = \pi_t^{\mathrm{NG}} \times \mathrm{FU}_t^{\mathrm{CHP},i} \tag{47}$$

$$\mathbb{C}_t^{\mathrm{CHP},i} \leq \pi_t^{\mathrm{CHP},i} \leq 2 \times \mathbb{C}_t^{\mathrm{CHP},i} \tag{48}$$

$$\mathbb{R}_{t,e}^{\mathrm{CHP},i} = \pi_{t,e}^{\mathrm{CHP},i} \times P_{t,e}^{\mathrm{CHP},i} \tag{49}$$

$$\mathbb{R}_{t,h}^{\mathrm{CHP},i} = \pi_{t,h}^{\mathrm{CHP},i} \times P_{t,h}^{\mathrm{CHP},i} \tag{50}$$

Eq. (47) is described the cost of power generation by CHP, and the respective price bid is shown in Eq. (48). Further, Eqs. (49) and (50) state the revenue of selling electrical and thermal powers generated by CHP.

GB constraints in H-MG i

The limits of the power generated by GB is given in Eq. (51), while Eq. (52) expresses the GB cost from generating thermal power. Similarly, Eq. (53) provides the amount of fuel consumed by GB and Eq. (54) is derived the price bid range for selling power.

$$0 \leq P_{t,h}^{\mathrm{GB},i} \leq \overline{P}_{t,h}^{\mathrm{GB},i} \tag{51}$$

$$\mathbb{C}_{t,h}^{\mathrm{GB},i} = \pi_{t,h}^{\mathrm{NG}} \times \mathrm{FU}_{t}^{\mathrm{GB},i} \tag{52}$$

$$\mathrm{FU}_{t}^{\mathrm{GB},i} = \frac{P_{t}^{\mathrm{GB},i}}{\zeta_{h}^{\mathrm{GB}}} \tag{53}$$

$$\mathbb{C}_{t,h}^{\mathrm{GB},i} \leq \pi_{t,h}^{\mathrm{GB},i} \leq 2 \times \mathbb{C}_{t,h}^{\mathrm{GB},i} \tag{54}$$

The revenue of selling thermal power by GB is shown in Eq. (55).

$$\mathbb{R}_{t,h}^{\mathrm{GB},i} = \pi_{t,h}^{\mathrm{GB},i} \times P_{t,h}^{\mathrm{GB},i} \tag{55}$$

5.2.4. Consumers constraints in H-MG i

DR constraints in H-MG i

Eq. (56) is determined that the value of shiftable power should be less than or equal to the sum of total consumed power minus the total generated power. Furthermore, Eq. (58) is represented that the DR limit between two consecutive intervals must not exceed a certain limit.

$$P_{t}^{\mathrm{DR}\text{-},i} \leq (P_{t}^{\mathrm{TCP},i} - P_{t}^{\mathrm{TGP},i}) \cdot X_{t}^{\mathrm{DR}\text{-},i} \tag{56}$$

$$P_{t}^{\mathrm{DR}+,i} \leq (P_{t}^{\mathrm{TGP},i} - P_{t}^{\mathrm{TCP},i}) \cdot (1 - X_{t}^{\mathrm{DR}\text{-},i}) \tag{57}$$

$$P_{t}^{\mathrm{DR}+,i} \leq k_{e} \times P_{t}^{\mathrm{NRL},i} \times (1 - X_{t}^{\mathrm{DR}\text{-},i}) \tag{58}$$

$$-k_{t} \leq (P_{t}^{\mathrm{DR}+,i} - P_{t-1}^{\mathrm{DR}+,i}) \leq k_{t} \tag{59}$$

ATL and AEL constraints in H-MG i

Eqs. (60) and (61) are the costs of buying electric and thermal power by AEL and ATL, wherein Eqs. (62) and (63) explain the price bid interval for buying power by AEL and ATL.

$$\mathbb{C}_{t,e}^{\mathrm{AEL},i} = \pi_{t,e}^{\mathrm{AEL},i} \times P_{t,e}^{\mathrm{AEL},i} \tag{60}$$

$$\mathbb{C}_{t,e}^{\mathrm{ATL},i} = \pi_{t,e}^{\mathrm{ATL},i} \times P_{t,e}^{\mathrm{ATL},i} \tag{61}$$

$$\lambda_{t,e}^{\mathrm{MCP}} \leq \pi_{t,e}^{\mathrm{AEL},i} \leq 2 \times \lambda_{t,e}^{\mathrm{MCP}} \tag{62}$$

$$\begin{gathered} \max(\pi_{t,h}^{\mathrm{TES}\text{-},i}, \pi_{t,h}^{\mathrm{CHP},i}, \pi_{t,h}^{\mathrm{GB},i}, \pi_{t,h}^{\mathrm{TSP},i}) \leq \pi_{t,h}^{\mathrm{ATL},i} \leq \\ 2 \times \max(\pi_{t,h}^{\mathrm{TES}\text{-},i}, \pi_{t,h}^{\mathrm{CHP},i}, \pi_{t,h}^{\mathrm{GB},i}, \pi_{t,h}^{\mathrm{TSP},i}) \end{gathered} \tag{63}$$

TD constraints in H-MG i

Eq. (72) presents the cost of buying thermal power by TD, where Eq. (73) states the offer price range.

$$\mathbb{C}_{t,h}^{\mathrm{TD},i} = \pi_{t,h}^{\mathrm{TD},i} \times P_{t,h}^{\mathrm{TD},i} \tag{64}$$

$$0 \leq \pi_{t,h}^{\mathrm{TD},i} \leq \min(\pi_{t,h}^{\mathrm{TES}\text{-},i}, \pi_{t,h}^{\mathrm{CHP},i}, \pi_{t,h}^{\mathrm{GB},i}, \pi_{t,h}^{\mathrm{TSP},i},) \tag{65}$$

REF constraints in H-MG i

The expenses of buying power by FER is derived in Eq. (69), while Eq. (70) is defined the offer price interval when purchasing energy.

$$\begin{cases} \text{if } \underline{T}^{\mathrm{REF},i} \leq T_{t}^{\mathrm{RET}} \leq \overline{T}^{\mathrm{REF},i} & X_{t}^{\mathrm{REF},i} = 0 \\ \text{Otherwise} & X_{t}^{\mathrm{REF},i} = 1 \end{cases} \tag{66}$$

$$X_{t}^{\mathrm{REF},i} = 1 \Longrightarrow P_{t,e}^{\mathrm{REF},i} = \overline{P}^{\mathrm{REF},i}, \quad T_{t}^{\mathrm{REF},i} = T_{t-1}^{\mathrm{REF},i} - T^{\mathrm{RED},i} \tag{67}$$

$$X_{t}^{\mathrm{REF},i} = 0 \Longrightarrow P_{t,e}^{\mathrm{REF},i} = 0, \quad T_{t}^{\mathrm{REF},i} = T_{t-1}^{\mathrm{REF},i} + T^{\mathrm{RED},i} \tag{68}$$

$$\mathbb{C}_{t,e}^{\mathrm{REF},i} = \pi_{t,e}^{\mathrm{REF},i} \times P_{t,e}^{\mathrm{REF},i} \tag{69}$$

$$0 \leq \pi_{t,e}^{\mathrm{REF},i} \leq \lambda_{t,e}^{\mathrm{MCP}} \tag{70}$$

DW constraints in H-MG i

Eqs. (73) and (74) express the cost for buying power by DW, and price bid scope for buying power, respectively.

$$\text{if } X_t^{\mathrm{DW},i} = 1 \Longrightarrow P_{t,e}^{\mathrm{DW},i} = \overline{P}^{\mathrm{DW},i}, \ \ \mathrm{DT}_t^{\mathrm{DW},i} = \mathrm{DT}_{t-1}^{\mathrm{DW},i} + 1 \tag{71}$$

$$\text{if } \mathrm{DT}_t^{\mathrm{DW},i} = \overline{\mathrm{DT}}^{\mathrm{DW},i} \Longrightarrow P_{t,e}^{\mathrm{DW},i} = 0, \ \ X_t^{\mathrm{DW},i} \tag{72}$$

$$\mathbb{C}_{t,e}^{\mathrm{DW},i} = \pi_{t,e}^{\mathrm{DW},i} \times P_{t,e}^{\mathrm{DW},i} \tag{73}$$

$$0 \le \pi_{t,e}^{\mathrm{DW},i} \le \lambda_{t,e}^{\mathrm{MCP}} \tag{74}$$

HHW constraints in H-MG i

Finally, the HHW limitations could be evaluated as below:

$$\begin{cases} \text{if } \underline{T}^{\mathrm{HHW},i} \le T_t^{\mathrm{HHW}} \le \overline{T}^{\mathrm{HHW},i} & X_t^{\mathrm{HHW},i} = 0 \\ \text{Otherwise} & X_t^{\mathrm{HHW},i} = 1 \end{cases} \tag{75}$$

$$X_t^{\mathrm{HHW},i} = 1 \Longrightarrow \begin{cases} P_{t,e}^{\mathrm{HHW},i} = \overline{P}^{\mathrm{HHW},i} \\ T_t^{\mathrm{HHW},i} = T_{t-1}^{\mathrm{HHW},i} + T^{\mathrm{INC},i} \end{cases} \tag{76}$$

$$X_t^{\mathrm{HHW},i} = 0 \Longrightarrow \begin{cases} P_{t,e}^{\mathrm{HHW},i} = 0 \\ T_t^{\mathrm{HHW},i} = T_{t-1}^{\mathrm{HHW},i} - T^{\mathrm{INC},i} \end{cases} \tag{77}$$

$$\mathbb{C}_{t,h}^{\mathrm{HHW},i} = \pi_{t,h}^{\mathrm{HHW},i} \times P_{t,h}^{\mathrm{HHW},i} \tag{78}$$

$$0 \le \pi_{t,h}^{\mathrm{HHW},i} \le \max(\pi_{t,h}^{\mathrm{TES\text{-}},i}, \pi_{t,h}^{\mathrm{CHP},i}, \pi_{t,h}^{\mathrm{GB},i}, \pi_{t,h}^{\mathrm{TSP},i},) \tag{79}$$

6. Results and discussion

In this section, the simulation results of each four methods is presented. The system under study has three H-MGs named as, *A*, *B* and *C*, which include different DER and consuming sources. The specifications are described further in Appendix B.

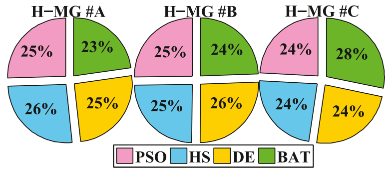
The total power generated by electrical and thermal DERs in each GB, and the total electrical power sold and purchased between GBs and retailers with four of optimization methods is illustrated in Fig. 5. As it is observed in Fig. 5(a), maximum power generated by electrical DERs in GB (#*A*) is obtained by HS method due to the absent of power transferring from GB to retailer. Further, the total power allocated for DR+ has the least value compared to other methods. The higher amount of total power produced in this H-MG facilitates to sell energy to other neighborhood H-MG, concurrently increasing the revenue of H-MG (#*A*). Besides, the conditions for H-MG (#*B*) is different compared to other H-MG, as the value of DE method is relatively higher when generating power, due to purchasing the power from another retailer. From Figs. 5(b) and 5(c), it is observed that GB #*B* in the PSO optimization method has a greater interaction with the retailer compared to other methods. Due to the average value of electrical MCP in PSO method is lower than other methods, GB #*B* facilitates the numerous consumers with lower MCP buying price from the retailer. Furthermore, the DR+ consumed power by HS method is 27% of the total consumed (DR+) power by other optimization methods. In particular, the HS method tempts to purchase more energy from the retailers to produce more RLD loads in the MO-TE model.

According to Fig. 5(a), in GB #*C*, the value of total power generated by BAT method is the maximum compared to other optimization methods. Moreover, the power exchange value with retailer for GB #*C* has the highest limit for BAT, as illustrated from Figs. 5(b) and 5(c). The reason is that, the value of sum DR- has reached its lowest possible limit with regards to other methods (6%), while about 26% of total DR+ power shared to BAT method which is a significantly higher value among the other implemented methods. Since the average value of electrical MCP in the BAT method is lower with respect to HS and DE methods, the consumers in this GB could receive the power for a lower price. In addition, it is noticeable that the minimum value of electrical MCP is obtained in the BAT method.

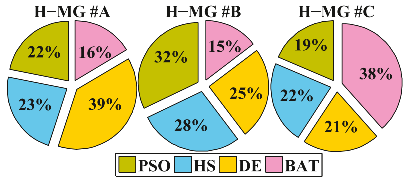
In contrast, the amount of the total power generated by thermal DER for each GB is shown in Fig. 5(d). In GBs #*A* and #*C*, most of thermal power is produced by HS method, while in GB #*B* the total energy is generated using BAT method. However, the average value of thermal MCP by HS and BAT methods is lower than other methods due to the occurrence of a smart selection on further power generation by thermal DER. This is because, the minimum value of thermal MCP is achieved in these methods and maximum value of thermal MCP is gained in DE and PSO methods which could lead to a significant increase in the thermal power cost. Therefore, less thermal power is generated by DE and PSO methods while optimizing the profit of GB owner and satisfying the consumer thermal power requirement.

In Fig. 6, the consumed load profile is presented for each GB. According to Fig. 6(a), the consumption peak value by PSO and BAT methods in GB #*A* has been shifted to non-peak intervals. In fact, the average of MCP value in peak intervals is high in every optimization methods. However, the consumers are managed to pay a less amount of price to GB owner and retailers when exchanging power, due to the participation of consumers in the DR program. This is when the total value of DR+ in BAT method is about 28% of total DR+ among the other types. In addition, it is expected that PSO method follows a similar pattern for consuming resources to increase the DR+ value. Evaluation expresses that about 26% of DR+ generation among implemented methods are shared by PSO.

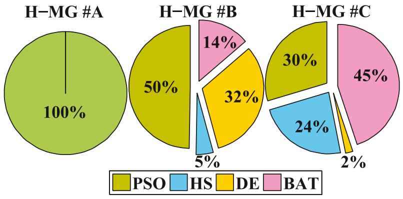
As evaluated in GB #*C*, the total values of DR- in DE and BAT are equal, which is nearly 28% of the total DR- proposed by all the methods. The minimum value of total DR in HS method represents the lack of shifting demand from one time interval with



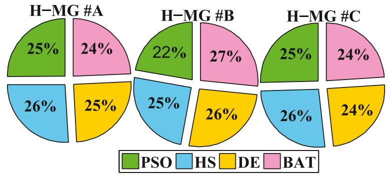
(a) The amount of total generated power in each GB



(b) The electrical power sold by the GBs to the retailers

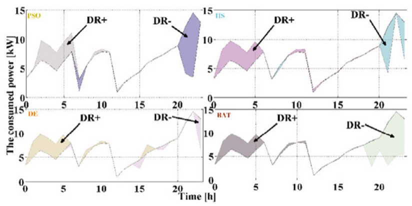


(c) The electrical power bought by the GBs from the retailers

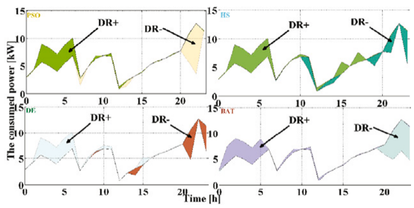


(d) The amount of total generated thermal power in each GB

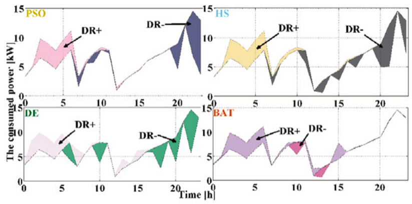
Fig. 5. The total amount of electrical and thermal powers consumed by each GB using different optimization methods.



(a) GB #A



(b) GB #B



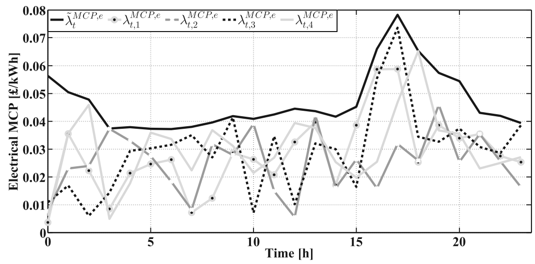
(c) GB #C

Fig. 6. Consumed load demand profile in the GBs.

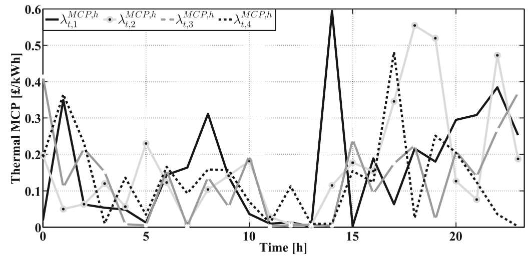
high price to another with much lower price. This is because, the cost of electricity production by the entire H-MGs contains the maximum value for all the methods due to a 28% decrement compared to the DE method, which facilities the minimum electricity production cost. The HS method is utilized to gain the maximum GB *#B* value of DR+, as a result of DR- value demonstrates a notable reduction by using this method. Due to high cost of generated power, the proposed algorithm desires to reduce the power consumption in the GB. Most significantly, although the amount of generation in the BAT method has the highest value after HS, the total value of DR- has become minimum relative to other methods. Therefore, BAT method has preferably increased the DR+ value. In GB *#C*, the DR+ and DR- values are maximum in the PSO method with regards to other types. In addition, PSO method has the minimum value of electricity cost after DE method.

It is concluded that, more value of DR+ is supplied by BAT method and meanwhile reduces the DR- value to minimum value. As discussed before, the electricity generation cost and the average electrical MCP in the BAT method compared to other methods is high during 24 h performance of the grid under study. Thereby, supplying the DRs during relevant times reduces the power cost for consumers.

Figs. 7(a) and 7(b) describe the values of electrical and thermal MCPs obtained from simulation by each optimization methods. In fact, Fig. 7(a) explains that MCP values in all approaches have been reduced to predicted MCP to occur in 100% of time period. At the



(a) Electrical MCP



(b) Thermal MCP

Fig. 7. MCP profile in each time interval under the 24 h performance of the system under study using different optimization methods.

beginning, PSO method has performed successfully in reducing the MCP compared to BAT method which the weakest performance is presented. In the morning, PSO approach shows a most effective performance in MCP reduction, while the worst functionality is occurred in HS method where the MCP increases for around 83%.

During the latter time intervals, HS performance was the worst performance among all the methods, as opposed to the functionality at the initial stage. The PSO method has achieved lower MCP value relative to DE (about 34%). Although PSO has the best operation during this time interval (afternoon), it has the worst performance among all the methods during the afternoon to evening. However, HS method has gained the best performance during afternoon to sunset where the electrical MCP has reached its minimum value, which Is nearly 78% of the time compared to PSO method. During the last few hours of the day, HS method has obtained a greater value for MCP which is about 22% of the time. Overall, the best performance for MO-TE structure over 24 h period has achieved by HS method, which is approximately 6%, 9% and 62% of times less MCP value respectively in comparison to PSO, BA and DE. In Fig. 7(b), expresses that the PSO method has a considerable proportion in decreasing the thermal MCP, at the beginning, and midnight to morning. Therefore, it has obtained the minimal value compared to other optimization methods.

The worst result during this time interval is for BAT, about 77% of the time because it gains a higher thermal MCP value as a result of utilizing PSO method. In the morning, the best performance is obtained by DE, while the PSO method has notably reduced the functionality due to the decline in thermal MCP by about 45% of the time. In the time period of 12:00 to 18:00, DE has presented the best performance compared to others. In contrast, BAT has a worse performance of 70% weaker than DE. Further, during the final hours of the day, BAT has the best performance relative to others. Considering all the GBs, performance of DE algorithm is 2% preferable than BAT, and 28% better than HS and PSO. Therefore, DE has the best performance in reducing the MCP value.

7. Conclusions

In this paper, an effective energy management algorithm based on MAS has proposed for several H-MGs connected in a neighborhood grid. Optimization algorithms were suggested in order to increase the DERs utilization while maximizing the profit for all the market players. Further, the DR strategy has improved the model efficiency and consumer profitability by shifting the demand from peak hours (high MCP) to non-peak hours (low MCP). Energy exchange among the GBs has influenced the competition in the power market while encouraging consumers to access different DERs. Moreover, the presence of active consumers (referred to as prosumers) has enhanced the total revenue. The main contributions of the proposed structure could be summarized as follows.

- The model has introduced an effective decision making strategy which is equally distributed among the players (consumers, prosumers and retailers) with improved participation in the H-MG.
- The simulation results have shown without shortage in the implemented scenarios that even with fast changes in the strategies of the players participating in the market, easily take their proper strategy without knowing the pricing date of other players. This performance has been obtained by the effect of other players on the MCP price.
- The difficulty in increasing the grid network and complexity of the decision making variables in the EMS based one MAS, has been eliminated by introducing a smart algorithm in optimization methods.
- The proposed structure has increased the awareness for all the market players about the participation of DR program with advanced management.

CRediT authorship contribution statement

Seyedeh Samaneh Ghazimirsaeid: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft. **Mansour Selseleh Jonban:** Formal analysis, Investigation, Writing – original draft, Review & editing. **Manthila Wijesooriya Mudiyanselage:** Writing – original draft, Writing – review & editing. **Mousa Marzband:** Validation, Formal analysis, Writing – review & editing, Supervision, Funding acquisition. **Jose Luis Romeral Martinez:** Visualization, Writing – review & editing. **Abdullah Abusorrah:** Visualization, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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Appendix A

See Algorithms 1 and 2.

Algorithm 1 EMS-MAS ALGORITHM (ELECTRICAL SECTION)

Require: ▷ **For all BAT method, PSO method, DE method, HS method**

▷ Hourly prediction data of MG, $\overline{\mathrm{SOC}}^x$, $\underline{\mathrm{SOC}}^x$, $\overline{P}^x_{e/h}$, $\underline{P}^x_{e/h}$, $\mathrm{E}^x_{\mathrm{Tot}}$, $\underline{T}^y$, $\overline{T}^y$, $\overline{P}^j_{e/h}$, $\underline{P}^j_{e/h}$, $\mathrm{T}^y_{\mathrm{INI}}$, $\mathrm{T}^{\mathrm{RED}}$, $\mathrm{T}^{\mathrm{INC}}$, $\zeta^j_{e/h}$, $\underline{T}^{\mathrm{HHW}}$, $\overline{T}^{\mathrm{HHW}}$, $\overline{E}^x$, $\underline{E}^x$, $\overline{E}^x$, $\underline{E}^x$, $\overline{\pi}^z$, $\underline{\pi}^z$, π^{NG}_t, $\tilde{\lambda}^{\mathrm{MCP}}_t$

▷ x∈ {ES+, ES-, EV+, EV-, TES+, TES-}
▷ y∈ {REF, HHW}
▷ j∈ {CHP, GB, TSP}
▷ z∈ $\{j, k, m, l\}$

while t ≤ 24 **do**

▷ **Electrical part**

$$P^{\mathrm{req}}_{t,e} = (P^{\mathrm{ESP}}_t - P^n_{t,e}) \tag{80}$$

if $P^{\mathrm{req}}_{t,e} \geq 0$ **then** ▷ **Excess Generation Section**

$$P^{\mathrm{Ex}}_{t,e} = (P^{\mathrm{ESP}}_t - P^{\mathrm{req}}_{t,e}) \tag{81}$$

if $P^{\mathrm{Ex1}}_{t,e} \geq P^{\mathrm{DR\text{-}}}_{t,e}$ **then**

$P^{\mathrm{DR+}}_{t,e}$= Responding to $P^{\mathrm{DR\text{-}}}_{t,e}$ completely (Eqs. (56)–(59))

$$P^{\mathrm{Ex2}}_{t,e} = (P^{\mathrm{Ex1}}_{t,e} - P^{\mathrm{DR+}}_{t,e}) \tag{82}$$

if $\underline{\mathrm{SOC}}_t \leq \mathrm{SOC} \leq \overline{\mathrm{SOC}}_t$ **then** Fully charged mode

$$P^{\mathrm{Ex3}}_{t,e} = (P^{\mathrm{Ex2}}_{t,e} - P^{\mathrm{ES}}_{t,e}) \tag{83}$$

if $P^{\mathrm{Ex3}}_{t,e} > 0$ **then**
Dedicating excess power to grid or EWH
else
Exit the loop
end if
else
Go to grid and EWH. Then, exit the loop
end if

else
$P^{\mathrm{DR+}}_{t,e} = P^{\mathrm{Ex1}}_{t,e}$ and exit the loop (Eqs. (56)–(59))
end if ▷ **Shortage Power Section**
end if
if $P^{\mathrm{req}}_{t,e} \geq \underline{P}^{\mathrm{CHP}}_{t,e}$ **then** ▷ Eqs. (44)–(46)
CHP enters to the circuit
if $P^{\mathrm{CHP}}_{t,e} \geq P^{\mathrm{req}}_{t,e}$ **then** Go to excess generation section
else
if $\mathrm{SOC}_t > \underline{\mathrm{SOC}}_t$ **then** ▷ Eqs. (34)–(36)
Discharging Mode
if $P^{\mathrm{req}}_{t,e} > 0$ **then**
if $P^{\mathrm{EV}}_{t,e}$, $P^{\mathrm{DW}}_{t,e} > 0$ **then** ▷ Eqs. (71)–(72) and (33)
$P^{\mathrm{EV}}_{t,e} + P^{\mathrm{DW}}_{t,e}$ = Buy power from Grid and exit the for loop
else $P^{\mathrm{DR-}}_{t,e} = P^{\mathrm{req}}_{t,e}$ and exit the for loop
end if $P^{\mathrm{DR-}}_{t,e} = P^{\mathrm{req}}_{t,e}$ and exit the for loop
else
$P^{\mathrm{EV}}_{t,e}$, $P^{\mathrm{DW}}_{t,e} > 0$
$P^{\mathrm{EV}}_{t,e} + P^{\mathrm{DW}}_{t,e}$ = Buy power from Grid and exit the for loop
end if
end if
end if
else
$P^{\mathrm{DR-}}_{t,e} = P^{\mathrm{req}}_{t,e}$ and exit the for loop
end if
return Return determine the optimum capacity and profit of the all players.

Algorithm 2 EMS-MAS ALGORITHM (THERMAL SECTION)

while t ≤ 24 **do**

$$P^{req}_{t,h} = (P^{ETP}_{t,h} + P^{CHP}_{t,h} - P^{n}_{t,h}) \tag{84}$$

if $P^{req}_{t,h} \geq 0$ **then** ▷ **Excess thermal Section**
if $\underline{SOC}_{t,h} \leq SOC_{t,h} \leq \overline{SOC}_{t,h}$ **then** ▷ Fully charged mode
if $P^{Ex1}_{t,h} = (P^{req}_{t,h} - P^{ES}_{t,h}) > 0$
Dedicating excess power to thermal dump ▷ Eq. (64)–(65)
else
Exit the loop **then**
end if
else
Dedicating excess power to thermal dump and exit the for loop
end if
else $P^{req}_{t,h} < 0$ ▷ **Shortage thermal Section**
$P^{req}_{t,h} \geq \underline{P}^{GB}$ ▷ Eq. (51)–(53)
Gas boiler enters to the circuit
if $P^{GB}_{t} > P^{req}_{t,h}$ **then**
Go to the excess thermal section
else $SOC_{t,h} > \underline{SOC}_h$ ▷ Eq. (27)–(29)
Discharging mode
if $P^{req}_{t,h} > 0$ **then**
Buy Power from Virtual Source and exit the for loop
else Exit the for loop
end if
Buy power from virtual source and exit the for loop
end if
end if
end while
return Return determine the optimum capacity and profit of the all players.

Appendix B

Name of DER	Variable	Value	Name of DER	Variable	Value
GB	ζ_h^{GB}	85%	HHW	$\overline{P}_{t,e}^{\mathrm{HHW}}$	0.5
	$\overline{P}_h^{\mathrm{GB}}$	12		$T_{\mathrm{INI}}^{\mathrm{HHW}}$, $\underline{T}^{\mathrm{HHW}}$	18
	$\underline{P}_h^{\mathrm{GB}}$	3.6		$\mathrm{T}^{\mathrm{INC}}$	6
CHP	$\zeta_{e2}^{\mathrm{CHP}}$	−94.6916	ES	$\overline{P}_{t,e}^{\mathrm{ES+}}$	30
	$\zeta_{e1}^{\mathrm{CHP}}$	0.358511		$\underline{P}_{t,e}^{\mathrm{ES+}}$	0.34
	$\overline{P}_e^{\mathrm{CHP}}$	8		$\overline{P}_{t,e}^{\mathrm{ES-}}$	30
	$\underline{P}_e^{\mathrm{CHP}}$	2		$\underline{P}_{t,e}^{\mathrm{ES-}}$	0.34
				$\underline{\mathrm{SOC}}^{\mathrm{ES}}$	0
				$\overline{\mathrm{SOC}}^{\mathrm{ES}}$	100%
DW	$\overline{P}^{\mathrm{DW}}$	0.42	Natural gas	π_t^{NG}	0.012
EV	$\overline{P}_{t,e}^{\mathrm{EV+}}$	3.2	HHW	$\overline{P}_{t,e}^{\mathrm{HHW}}$	0.5
	$\underline{P}_{t,e}^{\mathrm{EV+}}$	0		$T_{\mathrm{INI}}^{\mathrm{HHW}}$, $\underline{T}^{\mathrm{HHW}}$	18
	$\underline{\mathrm{SOC}}^{\mathrm{EV}}$	0		$\mathrm{T}^{\mathrm{INC}}$	6
	$\overline{\mathrm{SOC}}^{\mathrm{EV}}$	100%		$\overline{T}^{\mathrm{HHW}}$	36
REF	$P_{t,e}^{\mathrm{REF}}$	0.12	TES	$\overline{P}^{\mathrm{TES+}}$	14.4
	$\overline{T}^{\mathrm{REF}}$	9		$\underline{P}^{\mathrm{TES+}}$	0
	$\underline{T}^{\mathrm{REF}}$	3		$\overline{P}^{\mathrm{TES-}}$	14.4
	$T_{\mathrm{INI}}^{\mathrm{REF}}$	27		$\underline{P}^{\mathrm{TES-}}$	0
	T^{INI}	6			
DR	k_ϵ	5			
	k_t	5			

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